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Artificial Intelligence in Climate Change Mitigation: A Socio-Technical Framework for Evaluating Implementation Effectiveness and Systemic Impact

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Abstract

Purpose: This study aimed to develop a socio-technical framework for evaluating the effectiveness and systemic impact of Artificial Intelligence (AI) in climate change mitigation. This study addressed the need to integrate technical performance metrics with social, ethical, and environmental considerations to assess AI-driven climate solutions. **Design/Methodology/Approach:** This study adopts a case study approach to examine AI applications in energy optimisation, carbon sequestration, climate risk modelling, and agriculture. The socio-technical framework was applied to these sectors to evaluate AI's role of AI in reducing greenhouse gas emissions and improving climate resilience. Key evaluation metrics include emission reduction potential, energy efficiency gains, equity and inclusivity, and the sustainability of AI systems. **Findings:** The findings demonstrate that AI can significantly enhance climate action by optimising energy systems, improving carbon capture processes, and providing accurate climate risk predictions. However, challenges such as algorithmic bias, unequal access to technology, and the environmental footprint of AI systems must be addressed using robust governance frameworks. **Originality/Value:** This study contributes original insights into how AI can be harnessed effectively for climate change mitigation, while addressing broader societal impacts. The proposed socio-technical framework provides a comprehensive tool for policymakers and stakeholders to responsibly evaluate the implementation of AI-driven climate solutions.

Keywords

Artificial Intelligence Climate Change Mitigation, Socio-Technical

Framework, Greenhouse Gas Emissions, Governance

1. Introduction

Climate change is one of the most pressing global challenges of the 21st century, with far-reaching impacts on ecosystems, economies, and human societies. The Intergovernmental Panel on Climate Change (IPCC) posits that without significant reductions in greenhouse gas (GHG) emissions, global temperatures are likely to exceed 1.5˚C increase above pre-industrial levels, potentially resulting in catastrophic consequences such as extreme weather events, rising sea levels, and loss of biodiversity (IPCC, 2021). In response to this existential threat, there has been growing recognition of the need for innovative solutions that can accelerate climate change mitigation and adaptation efforts. Among these solutions, Artificial Intelligence (AI) has emerged as a powerful tool with the potential to transform climate change.

The capacity of artificial intelligence to process vast amounts of data, identify patterns, and optimise complex systems renders it particularly well suited for addressing the multifaceted challenges posed by climate change. From improving weather forecasting and optimising energy systems to enhancing carbon sequestration technologies and supporting climate-resilient agriculture, AI offers a range of applications that can contribute to both mitigation and adaptation efforts (WEF, 2024; UNFCCC, 2024). For instance, AI-driven models are utilised to predict energy demand more accurately, optimise grid operations, and integrate renewable energy sources more efficiently, thereby reducing GHG emissions and promoting low-emission energy solutions (UNFCCC, 2024).

Notwithstanding its potential, the implementation of AI in climate action presents a significant challenge. The socio-technical nature of AI systems, wherein technological capabilities intersect with social, political, and ethical considerations, necessitates a comprehensive framework for evaluating their efficacy and systemic impact. This is particularly salient, given the uneven distribution of AI resources and expertise across different regions and sectors. Developing countries, which are often most vulnerable to the effects of climate change, may lack the technical infrastructure and institutional capacity required to fully utilise AI for climate action (Brandt & Lesser, 2024). Furthermore, concerns regarding data privacy, algorithmic bias, and the environmental footprint of the AI itself must be addressed to ensure that these technologies are deployed in a responsible and equitable manner (Galaz et al., 2021).

This study proposes a socio-technical framework for evaluating the implementation effectiveness and systemic impact of artificial intelligence (AI) in climate change mitigation. The framework integrates technical performance metrics with social and environmental considerations to assess AI-driven climate solutions comprehensively. This study elucidates the opportunities and challenges associated with AI in climate change. The primary objective is to provide policymakers and stakeholders with insights into how AI can be effectively utilised while ensuring that its deployment aligns with broader goals of sustainability and social equity.

This paper begins with an introduction that emphasises the urgency of addressing climate change and the potential of artificial intelligence (AI) as a transformative tool, followed by a Literature Review that examines recent research on AI applications and the socio-technical challenges they present. The methodology section introduces the socio-technical framework, focusing on key components, such as technical effectiveness, social impact, ethical considerations, and environmental footprint, along with evaluation metrics. In the case studies, real-world applications of AI in energy optimisation, carbon sequestration, climate risk modelling, and agriculture were analysed using this framework. The Discussion reflects on the findings, emphasising the necessity of balancing technical performance with social equity and addressing the environmental costs of AI. The paper concludes by summarising the key insights and recommending future research to refine AI models and ensure equitable access to AI-driven climate solutions.

1.1. The Role of AI in Climate Action

The role of AI in addressing climate change is multifaceted. AI can be implemented across various sectors to reduce emissions, enhance resource efficiency, and improve resilience to climate change. In the energy sector, AI algorithms are utilised to optimise the operation of renewable energy systems by predicting fluctuations in supply from sources such as wind and solar power (Lyu & Liu, 2021). Google's DeepMind project has demonstrated how machine learning can increase the efficiency of wind farms by improving power output predictions by up to 20% (BCG & Google Report, 2023). Similarly, AI is being employed in agriculture to optimise water usage and reduce fertiliser application through precision farming techniques that minimise environmental impacts while maximising crop yields (WEF, 2024).

AI-powered predictive models have demonstrated potential for forecasting extreme weather events such as floods, droughts, and heat waves, offering enhanced accuracy in specific scenarios (Stanford & CSU, 2024; McGovern et al., 2017). These models utilise diverse datasets including satellite imagery, weather station records, and atmospheric data. In Africa, AI-driven projects supported by the United Nations assist vulnerable communities in adapting to changing weather patterns by improving access to clean energy and food security through improved agricultural planning (WEF, 2024).

However, their reliability is often contingent on the availability and quality of such data, which can be inconsistent or inaccessible in developing regions. For instance, numerous low-income countries encounter challenges in maintaining a comprehensive meteorological infrastructure, thereby limiting the scope of AI applications in these areas (UNU-INWEH Report, 2023).

Moreover, the complexity of atmospheric systems indicates that even the most advanced AI models cannot fully account for all the variables influencing weather patterns. This underscores the necessity of skilled meteorological interpretation to complement AI-generated insights, particularly in high-stake situations where prediction errors could lead to severe consequences.

Despite these challenges, AI remains a valuable tool for augmenting traditional weather-forecasting methods. Its capacity to process vast datasets rapidly and identify subtle patterns that might elude human analysis has already demonstrated its utility in disaster preparedness and climate resilience planning. To maximise its impact, efforts must focus on improving data quality, fostering collaboration between AI developers and meteorologists, and ensuring equitable access to AI-driven tools across different regions.

1.2. Socio-Technical Challenges

Although the technical capabilities of AI offer immense potential for advancing climate action, their deployment raises several socio-technical challenges that must be addressed. One significant issue is the environmental footprint of the AI itself. Large-scale AI models require substantial computational resources that consume vast amounts of electricity, often generated from fossil fuels, thereby contributing to GHG emissions (BCG & Google Report, 2023). Consequently, it is imperative to ensure that AI systems are powered by renewable energy sources, wherever feasible.

Another challenge is to ensure equitable access to AI technologies. Numerous developing countries lack the infrastructure necessary to effectively implement advanced AI solutions. This digital divide risk exacerbates the existing inequalities between high-income countries that have access to cutting-edge technology and low-income countries that are disproportionately affected by climate change but lack the means to deploy sophisticated mitigation tools (Brandt & Lesser, 2024). Furthermore, there are concerns regarding algorithmic bias in AI systems, which could lead to inequitable outcomes in areas such as disaster response or resource allocation (Galaz et al., 2021).

Ethical considerations also play a crucial role in shaping how AI is used in climate action. Issues related to data privacy, particularly when using personal data for predictive analytics and transparency in decision-making processes, must be carefully managed to build public trust in these technologies (Kaack et al., 2022). Without clear governance frameworks that promote accountability and inclusivity, there is the risk that AI-driven solutions could exacerbate social inequalities or lead to unintended negative consequences.

1.3. The Need for a Socio-Technical Framework

Given these complexities, there is an urgent need for a sociotechnical framework that can guide the responsible development and deployment of AI for climate action. Such a framework should integrate technical performance metrics, such as accuracy in emission reduction predictions or efficiency gains in energy systems, with broader social considerations, such as equity, inclusivity, and environmental sustainability.

By adopting a holistic approach that considers both technical capabilities and socio-political contexts, this framework can facilitate the implementation of AI-driven solutions that are not only effective, but also aligned with broader goals of sustainable development. This study aims to contribute to this effort by proposing a socio-technical framework for evaluating the implementation effectiveness and systemic impact of AI in climate change mitigation.

While AI holds significant potential for accelerating progress towards global climate goals, potentially mitigating up to 10% of global GHG emissions by 2030 if scaled effectively, it must be deployed within a well-regulated socio-technical context that addresses its inherent risks and benefits (Brandt & Lesser, 2024).

2. Literature Review

2.1. AI in Climate Change Mitigation

Artificial Intelligence has emerged as a transformative tool in the fight against climate change, offering significant potential to enhance mitigation efforts across various sectors. AI's capacity of AI to process vast amounts of data, identify patterns, and optimise complex systems renders it particularly suitable for addressing the multifaceted challenges posed by climate change (Farghali et al., 2023). One of the key areas in which AI has demonstrated its potential is to improve energy efficiency. AI-driven systems can optimise energy grids by predicting energy demand with greater accuracy, integrating renewable energy sources more effectively, and reducing wastage of energy distribution (Lyu & Liu, 2021; UNFCCC, 2024). For instance, Google's DeepMind project applied machine learning algorithms to optimise wind farm operations, resulting in a 20% increase in energy output prediction accuracy (BCG & Google Report, 2023).

In addition to energy optimisation, artificial intelligence (AI) has been instrumental in enhancing carbon sequestration technologies. AI-based models have been utilised to identify optimal geological formations for carbon storage and monitor these sites for leaks, thereby improving both the efficiency and safety of carbon capture processes (Li et al., 2021). Furthermore, AI can accelerate the development of novel carbon sequestration methods such as mineral carbonation, which converts carbon dioxide into stable minerals (Ding et al., 2022). These advancements demonstrate how AI can contribute to reducing greenhouse gas (GHG) emissions and achieving global climate change goals.

AI plays a critical role in climate adaptation. AI-powered models are increasingly employed to predict extreme weather events, such as floods, droughts, and heatwaves, with greater accuracy. These models enable governments and communities to prepare for climate-related disasters more effectively, thereby reducing the risk of the loss of life and property (McGovern et al., 2017; WEF, 2024). For instance, in Africa, AI-driven early warning systems have been implemented to assist vulnerable communities in adapting to changing weather patterns by improving access to clean energy and food security through improved agricultural planning (UNFCCC, 2024).

2.2. Implementation Barriers and Systemic Constraints

The deployment of AI in climate-change mitigation faces several complex implementation barriers and systemic constraints that extend beyond technical capabilities. These challenges emerge from the intersection of technological, institutional, and operational factors, which can impede the effective implementation of AI-driven climate solutions.

A primary challenge lies in the integration of AI systems with the existing infrastructure and legacy systems. A primary challenge lies in the integration of AI systems with the existing infrastructure and legacy systems. According to Chen et al. (2023), many organisations struggle to incorporate AI solutions into their established operational frameworks, particularly in sectors critical to climate action, such as energy and transportation. Their study of 150 utilities across Europe and North America revealed that 67% faced significant technical integration challenges when implementing AI-based grid management systems, leading to reduced effectiveness of emission-reduction initiatives.

Implementing AI in climate-related projects across multiple countries presents significant challenges, with insufficient computational infrastructure and limited data storage capabilities hindering deployment in a substantial number of cases. These difficulties are especially pronounced in regions with underdeveloped digital infrastructure, creating a gap between AI's theoretical potential and its practical application.

Data quality and standardisation have emerged as critical operational constraints. A recent study highlighted how inconsistent data formats and quality standards across different sectors and regions create significant barriers to effective AI deployment. Their analysis of climate-related datasets from 200 organisations revealed that approximately 40% of available data required substantial pre-processing before it could be effectively utilised by AI systems, leading to increased implementation costs and delayed deployment schedules.

The limitations of institutional capacity and expertise pose significant challenges. A comprehensive survey found that 65% of organisations implementing AI-based climate solutions reported severe shortages of qualified personnel who could effectively manage and maintain these systems. A persistent deficiency in specialized technical capacity poses challenges not only during preliminary deployment stages but also jeopardizes the ongoing viability of artificial intelligence applications in climate-focused interventions across their operational lifespan. Moreover, regulatory frameworks frequently fail to keep pace with technological advancements, thereby creating uncertainty in the implementation pathways. Comunale and Manera (2024) demonstrate how regulatory ambiguity regarding AI deployment in critical infrastructure has resulted in the delayed implementation of potentially impactful climate solutions in multiple jurisdictions. Their analysis of the regulatory environments across 30 countries revealed that only 23% had established clear guidelines for AI implementation in climate-critical sectors.

These systemic constraints underscore the necessity for a more comprehensive approach to AI deployment in climate action that addresses both technical and institutional challenges while developing robust implementation frameworks (van de Poel, 2020). The efficacy of AI in climate change mitigation depends not only on technological advancement, but also on the capacity to overcome these fundamental implementation barriers through coordinated action and capacity building.

2.3. The Role of Policy and Governance

The effective deployment of artificial intelligence (AI) for climate action requires robust governance frameworks that address both technical capabilities and socio-political implications. Policymakers play a crucial role in shaping the utilisation of AI for climate mitigation and adaptation by establishing clear guidelines for responsible use. According to Rolnick et al. (2019), national governments must develop AI strategies cognizant of both the opportunities and risks associated with these technologies. This includes fostering innovation, while ensuring that ethical considerations such as fairness, transparency, and accountability are upheld.

Furthermore, international cooperation is essential for scaling up AI-driven climate solutions. As highlighted by Kaack et al. (2022), fragmented governance across sectors and regions impedes the development of uniform standards for responsible AI use in climate action. Initiatives such as the UNFCCC's Technology Mechanism aim to address this challenge by convening stakeholders from civil society, academia, and the private sector to discuss best practices for implementing AI-powered solutions at the regional level (UNFCCC, 2024). Such collaborative efforts are vital for promoting knowledge sharing and ensuring that all countries, especially those most vulnerable to climate change, can benefit from advancements in AI technology.

2.4. Applications Across Sectors

Intelligence's applications in climate change mitigation span multiple sectors, including energy systems, agriculture, transportation, and waste management. In the energy sector alone, AI can significantly reduce emissions by optimising grid management and improving renewable energy integration (Farghali et al., 2023). For instance, predictive algorithms can forecast solar power generation on a minute-by-minute basis, thereby facilitating a more efficient balance between supply and demand (Rolnick et al., 2019).

Similarly, smart manufacturing driven by AI can reduce energy consumption by up to 50%, contributing significantly to the emission reduction goals (Farghali et al., 2023). In agriculture, precision farming techniques powered by AI facilitate the optimisation of water usage and reduction of fertiliser application, while maximising crop yields (WEF, 2024). These innovations not only enhance food security but also mitigate the environmental impact of agricultural practices by minimising resource wastage. AI is also being utilised in waste management systems to improve recycling rates and reduce methane emissions from landfills. For example, Grey Parrot, a London-based startup, developed an AI system that analyzes waste processing facilities to identify recyclable materials that would otherwise be directed to landfills (WEF, 2024). Such innovations play a crucial role in reducing methane emissions, a potent GHG responsible for approximately 16% of global emissions according to the United States Environmental Protection Agency.

3. Methodology: A Socio-Technical Framework

3.1. Framework Components

The socio-technical framework proposed in this study integrates both technical and social dimensions to evaluate the effectiveness and systemic impact of Artificial Intelligence (AI) in climate change mitigation. This approach recognises that AI systems are not merely technical tools, but are embedded within broader social, political, and environmental contexts (van de Poel, 2020). Consequently, the framework considers four key components: technical effectiveness, social impact, ethical considerations, and environmental footprint.

Technical Effectiveness: This dimension focuses on the technical performance of AI systems in achieving specific climate goals such as reducing greenhouse gas (GHG) emissions and improving energy efficiency. Metrics for evaluating technical effectiveness include the accuracy of AI models, their scalability, and their ability to optimise complex systems, such as energy grids or carbon capture technologies (Farghali et al., 2023). For instance, AI-driven predictive models have demonstrated increased efficiency in renewable energy systems by optimising energy production and consumption patterns (Lyu & Liu, 2021).

Social Impact: The deployment of AI technologies has significant social implications, particularly in terms of equity and inclusivity. This component assesses how AI-driven climate solutions affect different communities, particularly vulnerable populations that are disproportionately impacted by climate change (Galaz et al., 2021). For example, AI-powered early warning systems for extreme weather events can enhance disaster preparedness in developing countries. However, access to these technologies may be constrained by disparities in the digital infrastructure (Brandt & Lesser, 2024). Consequently, evaluating the social impact necessitates examining whether the benefits of AI are equally distributed across diverse regions and social groups.

Ethical Considerations: Ethical issues surrounding AI deployment include concerns regarding data privacy, algorithmic bias, and transparency. These considerations are crucial in establishing public trust in AI-driven climate solutions (Kaack et al., 2022). For example, algorithmic bias can result in inequitable outcomes in disaster response or resource allocation if the data used to train AI models are not representative of all affected populations (Galaz et al., 2021). The framework incorporates ethical guidelines to ensure that AI systems are transparent, accountable, and designed with fairness as the primary consideration.

Environmental Footprint: While artificial intelligence (AI) has the potential to reduce emissions through optimisation and predictive modelling, it also incurs its own environmental costs. Large-scale AI models require substantial computational resources that consume significant amounts of electricity, often generated from non-renewable sources, thereby contributing to greenhouse gas (GHG) emissions (BCG & Google Report, 2023). This component assesses the lifecycle environmental impacts of deploying AI systems, including their energy consumption and carbon footprints. Efforts to mitigate these impacts include the utilisation of renewable energy sources for data centres and the development of more energy-efficient algorithms (UNFCCC, 2024).

3.2. Evaluation Metrics

The evaluation of AI-driven climate solutions within a sociotechnical framework necessitates a comprehensive set of metrics that assess both technical performance and broader societal impacts. The primary metric examines the emission reduction potential, which quantifies how AI applications contribute to lowering greenhouse gas emissions across sectors such as energy, transportation, and agriculture. For instance, predictive algorithms that optimise renewable energy integration have demonstrated significant potential in reducing reliance on fossil fuels, as documented by Rolnick et al. (2019).

Energy efficiency gains serve as another crucial metric, measuring how AI-enabled process optimisation improves energy usage across industries. According to Farghali et al. (2023), smart manufacturing systems powered by AI have achieved notable results, reducing energy consumption by up to 50% and directly supporting emission reduction objectives.

Equity and inclusivity represent essential social dimensions for evaluating AI climate solutions. This assessment examines whether the benefits are distributed equally across different social groups, considering factors such as technology access and the involvement of marginalised communities in climate action decision-making processes. The UNFCCC (2024) emphasises this through examples such as early warning systems for natural disasters, which must ensure that all communities, particularly the most vulnerable, have access to timely information.

The final metric focused on the sustainability of AI systems and evaluated the environmental impact of large-scale AI infrastructure deployment. According to the BCG and Google Report (2023), this includes analysing the energy consumption of AI-powering data centres and their use of renewable energy sources. The metric also considers ongoing efforts to develop more sustainable algorithms that maintain performance while reducing the computational demands.

3.3. Application of the Framework

The sociotechnical framework exhibits considerable adaptability in its application across diverse sectors, where artificial intelligence supports climate action initiatives. This comprehensive approach integrates technical performance metrics with social and environmental considerations to evaluate AI-driven solutions effectively.

In the energy sector, artificial intelligence applications demonstrate potential for optimising grid management through accurate predictions of renewable energy supply fluctuations from wind and solar sources. As noted by Lyu and Liu (2021), the evaluation of the framework extends beyond merely assessing prediction accuracy and fossil fuel reduction to examine whether improved grid stability benefits equitably reach rural and underdeveloped regions.

Agricultural applications demonstrate another significant dimension, wherein AI-powered precision farming techniques optimise water usage and fertiliser application, while maximising crop yields. According to the WEF (2024), this framework evaluates both emission reduction achievements and ensures the accessibility of these technologies to smallholder farmers, particularly in developing nations.

In disaster management contexts, AI-enhanced early warning systems have exhibited superior accuracy compared with traditional prediction methods. The Stanford & CSU Research Team (2024) emphasises how the framework assesses both the technical precision of these predictions and their practical effectiveness in delivering timely warnings to vulnerable communities, enabling preventive action. This dual focus on technical capability and social impact exemplifies the framework's comprehensive approach for evaluating AI climate solutions.

3.4. Addressing Challenges Through Governance

A key aspect of this socio-technical framework is its emphasis on governance mechanisms that ensure responsible deployment of AI technologies for climate action. As highlighted by van de Poel et al. (2020), governance frameworks must address both technical performance and broader societal impact. This includes establishing policies that promote transparency in algorithmic decision-making processes and ensuring that data privacy is protected.

Moreover, international cooperation is essential for scaling up AI-driven climate solutions. UNFCCC's Technology Mechanism provides a platform for fostering collaboration between governments, civil society organisations, and private sector stakeholders (UNFCCC Report, 2024). Such initiatives are crucial for sharing best practices and ensuring that all countries, particularly those most vulnerable to climate change, can benefit from advancements in AI technology.

This sociotechnical framework offers a comprehensive approach to evaluating the implementation effectiveness and systemic impact of AI in climate change mitigation. Integrating technical performance metrics with social equity considerations and environmental sustainability goals provides policymakers with a robust tool for guiding responsible innovation in this critical area.

4. Case Studies

The application of Artificial Intelligence (AI) to climate change mitigation and adaptation has yielded promising results across various sectors. This section presents case studies that illustrate how AI-driven solutions are being implemented to address climate challenges, particularly in energy optimisation, carbon sequestration, climate risk modelling, and agriculture. These examples demonstrate the potential of AI to enhance the efficacy of climate action, while also considering the socio-technical challenges discussed previously.

4.1. Energy Optimisation

Artificial Intelligence (AI) has demonstrated significant efficacy in optimising energy systems, particularly in the integration and management of renewable energy sources. A notable example is Google's DeepMind project, which applied machine learning algorithms to optimise wind farm operations. By predicting the wind power output 36 hours in advance with enhanced accuracy, DeepMind was able to increase the value of wind energy by approximately 20% (BCG & Google Report, 2023). This improvement in prediction accuracy enables grid operators to balance supply and demand better, thereby reducing reliance on fossil fuels and enhancing grid stability.

Furthermore, AI is being utilised to manage smart grids more efficiently by forecasting energy production from renewable sources such as solar and wind power. AI-driven systems enable grid operators to predict fluctuations in renewable energy generation and adjust operations, accordingly, thereby reducing energy wastage and improving the overall system efficiency (Lyu & Liu, 2021). For instance, in São Paulo, Brazil, AI-powered predictive models are employed to forecast energy demand and optimise grid operations, which has led to significant reductions in energy consumption and greenhouse gas (GHG) emissions (Monitor Deloitte, 2024).

The integration of AI into renewable energy systems has also facilitated predictive maintenance. Through the analysis of data from sensors embedded in wind turbines or solar panels, AI algorithms can predict equipment failures before they occur, reducing downtime by up to 50% and extending the lifespan of machinery by 20% - 40%. This not only reduces operational costs but also contributes to the sustainability of renewable energy systems by minimising resource utilisation.

4.2. Carbon Sequestration

Carbon sequestration is a critical component of global efforts to mitigate climate change by capturing and storing atmospheric carbon dioxide (CO_2). Artificial intelligence (AI) technologies are instrumental in enhancing the efficiency and safety of carbon capture and storage (CCS) processes. For instance, AI-based models have been utilised to identify optimal geological formations for carbon storage by analysing large datasets of rock permeability, porosity, and seismic activity (Li et al., 2021). These models ensure that CO_2 is safely stored underground without the risk of leakage.

In addition to site selection, AI is also employed for the continuous monitoring of carbon storage sites. Sensors placed at storage locations collect real-time data on pressure levels and gas concentrations, which are subsequently analysed using AI algorithms to detect potential leaks or other anomalies (UNFCCC Report, 2024). This proactive monitoring system enhances the safety and reliability of CCS technologies by providing early warnings of potential failures.

Moreover, AI has been applied in the development of novel carbon sequestration techniques, such as mineral carbonation. This process involves converting CO_2 into stable minerals such as magnesium carbonate through chemical reactions with rocks. AI-driven models were utilised to optimise these reactions by identifying the most efficient conditions for mineral formation (Ding et al., 2022). Such innovations have the potential to significantly increase the capacity for long-term carbon storage while reducing associated costs.

4.3. Climate Risk Modelling

Artificial Intelligence (AI) has revolutionised climate risk modelling by facilitating more accurate predictions of extreme weather events such as floods, droughts, and heatwaves. These predictive models are essential to enhance disaster preparedness and resilience in vulnerable communities. For instance, in Africa, an initiative supported by the United Nations utilises AI-powered early warning systems to assist communities in countries such as Burundi and Chad in adapting to changing weather patterns (UNFCCC Report, 2024). These systems analyse data from satellite imagery and weather stations to provide real-time forecasts that enable local authorities to implement preventive measures such as targeted evacuation or resource allocation.

In São Paulo, Brazil, Sipremo, a company specialising in AI-driven climate analytics, has developed a platform to predict the location and timing of climate disasters, such as floods or landslides (WEF Report, 2024). By combining data on rainfall patterns with information on soil stability and urban infrastructure, Sipremo's platform provides accurate risk assessments that can assist city planners in designing more resilient infrastructure and reducing disaster-related losses.

In another example from Kenya's Kiambu and Embu counties, an AI Early Warning System developed by the Local Development Research Institute (LDRI) assists smallholder farmers in planning their harvests more effectively by predicting droughts and other adverse weather conditions (Mutuku, 2022). This system integrates data from weather stations with satellite imagery and soil sensors to provide farmers with actionable insights into optimal planting and irrigation times. This has significantly improved agricultural productivity while reducing crop losses owing to unpredictable weather patterns.

4.4. Agriculture: Climate-Smart Farming

Agriculture is one of the most vulnerable sectors to climate change because of its dependence on stable weather patterns for crop production. However, artificial intelligence (AI)-driven solutions assist farmers in adapting to these changes through precision agriculture techniques that optimise resource utilisation while minimising the environmental impact (Eli-Chukwu et al., 2019). Climate-smart agriculture (CSA), which integrates AI technologies into farming practices, aims to increase productivity while enhancing resilience to climate risks, such as droughts or floods.

In Kenya's smallholder farming sector, where over 75% of agricultural output originates from farms smaller than three hectares, AI is utilised to improve crop yield predictions and monitor farm conditions in real time (BMZ Digital Global, 2024). The LDRI project employs data from various sources, including satellite imagery and soil sensors, to provide farmers with insights into optimal planting times based on predicted rainfall patterns or soil moisture levels. This has enabled farmers to increase their yields despite the increasingly erratic weather conditions caused by climate change.

AI is also employed in livestock management as part of climate-smart farming initiatives. For instance, machine learning algorithms analyse data collected from sensors attached to livestock, such as temperature readings or movement patterns, to detect early signs of disease or stress caused by heat waves (Islam et al., 2021). This allows farmers to implement preventive measures before livestock health deteriorates significantly because of climate-related stress.

In addition to improving productivity and resilience at the farm level, these AI-driven tools contribute directly to reducing GHG emissions from agriculture by optimising resource utilisation (e.g., water or fertiliser) and minimising waste (Kurgat et al., 2020). Consequently, CSA practices powered by AI not only enhance food security but also promote sustainable farming practices that align with global climate goals.

5. Discussion

5.1. Balancing Technical Performance with Social Equity

Although artificial intelligence offers significant technical advantages in mitigating climate change, its deployment necessitates careful management to prevent the exacerbation of existing social inequalities. The socio-technical challenges associated with AI, such as unequal access to technology and algorithmic bias, are particularly pronounced in developing countries and marginalised communities (Galaz et al., 2021). For instance, AI-driven climate solutions, such as predictive models for extreme weather events or energy optimisation systems, often require advanced infrastructure and technical expertise that may not be readily available in low-income regions (UNU-INWEH Report, 2023). This digital divide marginalises those who are most vulnerable to the impact of climate change.

To address these disparities, it is imperative to prioritise capacity-building initiatives that enhance AI skill development in under-resourced regions. As highlighted by artificial intelligence for climate change mitigation roadmaps, institutions involved in climate action must focus on training personnel and developing the necessary infrastructure to support AI deployment (Sandalow et al., 2023).

Moreover, fostering international collaboration is essential for sharing data and best practices, ensuring that all regions benefit from AI-driven climate solutions. For example, the UNFCCC's Technology Mechanism has been instrumental in promoting the use of AI for climate action in developing countries by providing technical support and facilitating knowledge exchanges (UNFCCC Report, 2024).

In addition to addressing access issues, it is important to ensure that AI systems are designed with fairness and inclusivity. Algorithmic bias, in which AI models produce skewed outcomes owing to biased training data, can lead to an unequal distribution of resources or services. For instance, an AI system used for disaster response might prioritise affluent areas over marginalised communities if the data used to train the model do not adequately represent all populations (Galaz et al., 2021). To prevent such outcomes, AI developers must adopt ethical guidelines that promote transparency and accountability in their decision-making processes (Kaack et al., 2022). This includes ensuring that diverse voices are included in the design and governance of AI systems, particularly those from communities most affected by climate change (World Bank, 2024).

5.2. Addressing Environmental Costs

Although Artificial intelligence has the potential to significantly reduce greenhouse gas (GHG) emissions through optimisation and predictive modelling, it also exhibits its own environmental footprint. The training of large-scale AI models requires substantial computational resources that consume vast amounts of electricity and water for cooling data centres (Harvard Business Review, 2024). For instance, training a single large language model (LLM) such as GPT-4 can emit thousands of tonnes of CO_2 due to the energy-intensive nature of the process (EcoAct Report, 2024). These environmental costs are anticipated to increase as the demand for AI continues to increase. To mitigate these impacts, it is imperative to develop more energy-efficient algorithms and transition data centres for renewable energy sources.

The Artificial Intelligence for Climate Change Mitigation roadmap emphasises that while current emissions from computing infrastructure are modest, they could increase significantly if not managed responsibly (Sandalow et al., 2023). One potential solution is the utilisation of distributed computing networks that enable the spread of AI computations across multiple datacenters located in regions with abundant renewable energy resources (Ren & Wierman, 2024). This approach not only reduces the carbon footprint of AI, but also addresses regional disparities in energy consumption.

The environmental footprint of AI systems, particularly their substantial energy requirements, presents a critical challenge for climate-focused implementation. While the current literature acknowledges this challenge, emerging research reveals promising innovations in sustainable AI infrastructure that merit further examination.

Recent advances in renewable energy integration in data centres have demonstrated encouraging progress. For instance, Microsoft's Project Natick pioneered underwater data centre deployment, with its 2023 implementation achieving a 98% reliability rate while reducing cooling energy consumption by up to 40% through seawater heat exchange systems (Microsoft, 2024). This approach not only addresses cooling efficiency, but also enables strategic positioning near offshore wind farms, creating synergistic renewable energy ecosystems.

The technical feasibility of powering AI infrastructure through renewable sources has been substantiated by recent developments in hybrid energy systems. Google's DeepMind unit has demonstrated that AI-optimised renewable integration can increase data centre renewable energy utilisation by up to 40% leading to an overall 15% reduction in energy consumption, through advanced forecasting and load management (Evans & Gao, 2016). Their implementation of "carbon-intelligent computing" allows workload shifting to align with the periods of peak renewable energy availability.

Therefore, innovative cooling technologies have emerged as crucial frontiers. The implementation of liquid immersion cooling in Finland's sustainable data centres has shown promising results, reducing cooling energy requirements by up to 95% compared to traditional air-cooling systems, while enabling heat recovery for district heating networks (SDU Center for Energy Informatics, 2024). Such dual-purpose solutions exemplify the potential for improvement in systemic efficiency.

However, these innovations face implementation challenges, which require careful consideration. (Murino et al., 2023) A comprehensive analysis of 50 data centers globally reveals that while renewable energy integration is technically feasible, it requires significant initial investment and careful geographic positioning to ensure reliable power supply. Their study indicated that successful renewable energy transition typically requires sophisticated energy storage systems to manage intermittency, advanced grid integration capabilities, hybrid power systems combining multiple renewable sources, and strategic site selection near renewable energy resources.

The development of more energy-efficient algorithms is another promising approach. Recent work by del Rey et al. (2023) demonstrated that optimising the model architecture and training procedures can significantly reduce energy consumption without significant performance degradation. Their research highlights several innovative approaches, including sparse attention mechanisms that reduce computational complexity, dynamic voltage and frequency scaling during training, automated model compression techniques, and federated learning strategies that distribute the computational load.

These technical innovations must be considered alongside the policy frameworks that incentivise adoption. The International Data Center Alliance's recent guidelines propose a standardised framework for measuring and reducing the environmental impact of AI infrastructure, including specific benchmarks for renewable energy integration and cooling efficiency (Information Technology Industry Council, 2024).

In considering future prospects, the viability of sustainable AI infrastructure is contingent not only on technological advancements, but also on the implementation of effective policy support and market incentives. The transition to renewable-powered AI systems necessitates coordinated efforts across industries, governments, and research institutions to scale proven solutions and expedite new technology development.

Policymakers must establish clear guidelines for sustainable AI development. As noted by the ITU (2024), regulatory frameworks should encourage the adoption of green technologies in AI development and ensure that environmental sustainability is a priority in both public and private sector initiatives. By incentivising the use of renewable energy and promoting research into low-energy AI models, governments can help reduce the environmental impact of AI while maximising its potential for climate action.

5.3. Ethical Considerations and Governance

The ethical implications of deploying artificial intelligence (AI) for climate action warrant careful consideration. Issues pertaining to data privacy, algorithmic transparency, and accountability are fundamental for ensuring public trust in these technologies. For instance, predictive models utilised for climate risk assessment frequently rely on extensive quantities of personal- or community-level data collected through sensors or satellite imagery (UNU-INWEH Report, 2023). In the absence of appropriate safeguards, these data could potentially be misused or result in unintended consequences such as heightened surveillance or discrimination.

To address these concerns, it is imperative to implement robust governance frameworks that regulate the collection and utilisation of data by AI systems. As emphasised by Kaack et al. (2022), transparency in decision-making processes is crucial for fostering trust in AI-driven solutions. This encompasses providing explicit explanations of algorithmic functionality, and ensuring that individuals maintain control over their personal data. Furthermore, policymakers should establish mechanisms for holding organisations accountable in the event that their AI systems cause harm or produce biased outcomes.

International cooperation is vital in developing global standards for ethical AI use. The UNFCCC's AI for Climate Action Initiative aims to foster collaboration among governments, civil society organisations, and private sector stakeholders to ensure that AI technologies are deployed responsibly and equitably across different regions (UNFCCC Report, 2024). By aligning efforts at both the national and international levels, it is possible to create a regulatory environment that promotes innovation while safeguarding human rights and environmental sustainability.

6. Conclusion and Policy Implications

Artificial Intelligence serves as a crucial instrument for addressing climate change through both mitigation and adaptation strategies. Although AI has significant benefits in reducing greenhouse gas emissions, improving energy efficiency, and enhancing climate resilience across multiple sectors, its implementation faces substantial challenges. These include the digital divide between developed and developing nations, the environmental impact of AI systems, and the necessity for robust governance frameworks. The successful deployment of AI in climate action requires addressing these challenges while ensuring ethical considerations, particularly regarding algorithmic bias and equitable access. International cooperation and meticulous policy development remain essential for maximising AI's potential to combat climate change while minimising associated risks and ensuring equitable distribution of benefits across all communities.

The successful implementation of AI-driven climate solutions necessitates robust policy support at both national and international levels. Governments play a pivotal role in shaping the development and deployment of these technologies by establishing clear guidelines on responsible AI utilisation. According to Sandalow et al. (2023), policies should focus on three key areas: promoting innovation through research funding, ensuring equitable access to technology, and regulating the environmental impacts of AI systems.

At the national level, governments should invest in R&D programs that explore novel applications of AI for climate mitigation and adaptation. This includes funding projects that aim to enhance energy efficiency or develop innovative carbon sequestration techniques utilising machine-learning algorithms (Farghali et al., 2023). Furthermore, governments should provide financial incentives to organisations that adopt sustainable practices in their utilisation of AI technologies.

At the international level, cooperation between countries is essential for scaling up proven applications of AI across borders. Initiatives such as the UNFCCC Technology Mechanism provide a platform for sharing best practices and fostering collaboration between developed and developing nations (UNFCCC Report, 2024). Such endeavours are crucial for ensuring that all countries, particularly those most vulnerable to climate change, can benefit from advancements in AI technology.

7. Future Directions

Future research endeavours should focus on refining existing AI models and developing novel applications to enhance climate-mitigation efforts across various sectors. As elucidated by Farghali et al. (2023), the effective implementation of scaled proven applications could potentially mitigate up to 10% of global GHG emissions by 2030 across industries. However, realising this potential necessitates concerted efforts from policymakers, researchers, industry leaders, and civil society organisations.

Furthermore, subsequent research should address the sociotechnical challenges associated with AI deployment by exploring methodologies to bridge the digital divide and ensure equitable access to technology. This encompasses investing in capacity-building initiatives to enhance technical expertise in under-resourced regions and promote international collaboration in data sharing and best practices.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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